Quality versus Quantity Effects of Pesticides:

Joint Estimation of Quality Grade and Crop Yield

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Abstract. While the capacity of pesticides to protect output from losses is well established, the contribution of pesticides to prevention of quality damage has been less extensively documented. The relative importance of the quality and quantity effects of pesticides has received even less attention. We investigate the relative effects of the three major classes of pesticides—insecticides, herbicides, and fungicides—on the quantity and quality of output. To do so, we build on our previous work to develop a new econometric estimator for estimating quality and quantity of output simultaneously when quality is measured in terms of discrete grades. We apply that estimator using a panel of data from Japanese wheat production for the period 1995-2006. The estimated parameters of the model indicate that the quality effects of fungicides and fertilizer are substantial: Increases in quality account for two-fifths of the overall marginal revenue product of fertilizer and close to a fifth of the overall marginal revenue product of fungicides. The magnitude of the effect of fertilizer on wheat quality attests to the importance of kernel size and weight in determining grade. Similarly, the magnitude of the effect of fungicides on wheat quality speaks to the importance of disease control in wheat production.

Keywords: grading standards, pesticides, fertilizers, productivity, climate change

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While the capacity of pesticides to protect output from losses is well established, the contribution of pesticides to prevention of quality damage has been less extensively documented. The relative importance of the quality and quantity effects of pesticides has received even less attention. This paper investigates the relative effects of the three major classes of pesticides—insecticides, herbicides, and fungicides—on the quantity and quality of output. To do so, we develop a new econometric estimator and apply it using data from Japanese wheat production. The estimated parameters of the model indicate that the quality and quantity effects of fungicides are substantial, highlighting the importance of disease control in wheat production. Insecticides and herbicides, in contrast, have no statistically discernible effect on either quality or yield.

Quality in agriculture is typically measured using discrete grades, which allows crops from different producers to be aggregated, thereby facilitating marketing (Cronon 1991). Grades are typically based on observable characteristics such as size, shape, color, blemishes, disease damage, and the presence of contaminants (weed seeds, insect parts, etc.), many of which can be influenced by pesticide use. Reliance on grading standards on observable characteristics has been controversial, at least for some fruits and vegetables where blemishes and other superficial aspects of appearance have no effect on taste, texture, or other attributes thought to be truer measures of quality such as scarring of citrus from mites and thrips (van den Bosch et al. 1975) and FDA standards for insect parts in fruit and vegetable crops ranging from raspberries and strawberries to broccoli and spinach to processed apple, cherry, tomato, and peanut products (Pimentel and Pimentel 1980). Disease damage, the presence of contaminants like weed seeds or insect parts, and other attributes typically used in grading wheat are less controversial, since they have obvious connections to either sanitation or to performance in different uses.

Empirical evidence regarding the role of pesticides in determining quality grades is quite limited, however. Babcock, Lichtenberg, and Zilberman (1992) show that fungicides, but not insecticides, affect grading of apples in North Carolina. Starbird's (1994) simulation study shows that processor's tolerances for fruitworm likely lead to more intensive insecticide use on processing tomatoes in California. Lichtenberg (1997) shows theoretically how grading standards create incentives for pesticide use and conducts a simulation showing that grading standards for apples may induce lower fungicide use under reasonable conditions. Kawasaki and Lichtenberg (2014) show that fungicide use increases the shares of Japanese wheat receiving high and medium quality grades while reducing the share receiving a low quality grade.

Estimating the determinants of quality grade is challenging for two reasons: (a) each grade category has a strict ordered nature (e.g. grade 1 is superior to grade 2) and (b) we typically observe the shares (fractions) of output falling into each of grading categories. A simple linear regression is not appropriate when the outcome of interests is grade shares. Kawasaki and Lichtenberg (2014) develop a methodology for estimating the determinants of grade shares that accounts for both ordered and fractional nature of outcomes, but ignores the determinants of quantity (yield). We extend their ordered fractional model by incorporating it into a simultaneous equation system in which quality and quantity effects are estimated jointly. Joint estimation enables more efficient estimation and hypothesis testing which compares the size of quantity and quality effects. Correlated random effects are used to control for unobserved time-invariant heterogeneity. Pesticides and fertilizer are treated as endogenous. The model is estimated in two stages using a control function approach to correct for endogeneity, with either input prices or neighbors' lagged input used as instruments in the first stage regressions. We use the estimated parameters of the model to calculate the marginal contributions of pesticides, fertilizer, varietal choice, and climate to overall output value via changes in the quality and quantity of output.

The estimated parameters of these models indicate that fungicides increase both the quality and quantity of output. The quality effects of fungicides are substantial, accounting for 18% of the contribution to overall revenue, depending on the functional specification. Put another way, the marginal contribution of fungicides to wheat revenue by improving its quality is on the order of 21% of the marginal contribution due to yield increases. This finding highlights the key role played by disease control in wheat production and thus the critical importance of addressing rising threats like the spread of new highly virulent stem rust races and likely increases in fusarium ear blight and other wheat diseases due to climate change. The effects of fertilizer on quality and yield are substantially smaller at the margin, but fertilizer's effect on quality is much larger relative to its yield effect than is the case for fungicides: The quality effects accounts for 31% of the contribution to overall revenue. Neither insecticides nor herbicides have a statistically significant effect on either yield or quality.

The System Ordered Fractional Estimator

The ordered fractional (OF) model developed by Kawasaki and Lichtenberg (2014) estimates the determinants of quality when quality is measured by discrete grades. Specifically, their estimator deals with the case where output is sorted and divided into multiple discrete grades, so that the outcome—shares of output in each grade—is both ordinal and fractional in nature. In this section, we extend the OF model to encompass the total quantity of output as well as the shares falling into each possible quality grade. We begin with a base case of cross-section data in which all regressors are exogenous. We then extend the model to panel data and to situations in which some explanatory variables are endogenous.

Base Model—Cross Section Data with Exogenous Regressors

While our estimator is quite general, we discuss it in terms of an agricultural commodity. Let Q_{2i} denote the quantity of a crop harvested on farm $i = 1, \ldots, N$. The crop is packed into $c = 1, \ldots, C_i$ containers of equal capacity or weight. Each container is sampled and given one of $g = 1, \ldots, G$ discrete quality grades (listed in ascending order) to each container based on a weighted combination of characteristics observed in that sample. For Japanese wheat, those characteristics include weight, kernel size, moisture content, mold damage, and appearance (Table 1). The econometrician observes the farm-level output Q_{2i}, the shares of output (fraction of all containers) in each grade s_{gi} and inputs $\mathbf{X}_i$ that influence potential crop quantity and quality that farm i produce. We are interested in the effects of those inputs on the amount of output and distribution of quality as measured by the shares of output in each grade. The observed grade shares $\mathbf{s}_i \equiv (s_{1i}, s_{2i}, \ldots, s_{Gi},)$ have two important characteristics: (1) they are ordered and (2) each share s_{gi} is measured as a fraction so that its value lies between 0 and 1, inclusive.

We assume that the grade assigned to each container is determined by an inherent quality index whose constituent parts are influenced by members of the set of inputs. Let Q_{1ic} denote the latent quality index (unobservable to the econometrician) of container c produced on farm i, a function of inputs $\mathbf{x}_1$ (subset of $\mathbf{X}$) and normally distributed random factors u_1:

$$(1)\quad Q_{1ic} = \mathbf{x}_{1i}\boldsymbol{\beta}_1 + u_{1ic},$$

where $\boldsymbol{\beta}_1$ is the parameter to be estimated. Since the units in which Q_1 is defined are arbitrary, we let the variance of u_1 be scaled to one. A container is given grade g if its quality index Q_1 exceeds some threshold μ_{g-1} but falls below the threshold for the next higher grade μ_g, so that the probability of a container receiving grade g is $\Pr(\mu_{g-1} \leq Q_{1ic} < \mu_g) = \Pr(\mu_{g-1} - \mathbf{x}_{1i}\boldsymbol{\beta}_1 \leq u_{1ic} < \mu_g - \mathbf{x}_{1i}\boldsymbol{\beta}_1) = \Phi(\mu_g - \mathbf{x}_{1i}\boldsymbol{\beta}_1) - \Phi(\mu_{g-1} - \mathbf{x}_{1i}\boldsymbol{\beta}_1)$ where Φ denotes the standard normal cumulative distribution. The threshold parameters are monotonically increasing ($\mu_g < \mu_{g+1}$, $\mu_0 = -\infty$ and $\mu_G = \infty$). Identification of threshold parameters requires excluding a constant term in equation (1).

Assuming that the containers are filled randomly (i.e., not sorted according to the farmer's observation of attributes that determine grade), the probability of receiving a given grade is the same for all containers and thus the expected share of farm *i*'s total output receiving grade *g* should equal this probability,

$$(2)\quad p_{gi} \equiv E(s_{gi} \mid \mathbf{x}_{1i}) = \Phi(\mu_g - \mathbf{x}_{1i}\boldsymbol{\beta}_1) - \Phi(\mu_{g-1} - \mathbf{x}_{1i}\boldsymbol{\beta}_1), \quad (g = 1, \ldots, G).$$

Let C_{gi}, denote the number of containers of grade g produced on farm i, and C_i denote the total number of containers ($C_i = \sum_{g=1}^{G} C_{gi}$). Then the likelihood L_i (probability density) of the grade composition observed on farm i is given by the multinomial distribution:

$$(3)\ L_i \equiv f(\mathbf{s}_i \mid \mathbf{x}_{1i}) = \frac{C_i\,!}{\prod_{g=1}^{G} C_{gi}!} \cdot \prod_{g=1}^{G} p_{\mathrm{gi}}^{C_{\mathrm{gi}}}\ .$$

Now consider total output produced on the farm, $Q_{2i} = \omega \sum_{g=1}^{G} C_{gi} = \omega C_i$, where ω is the weight of a single container. We assume that output is a linear-in-parameters function of a vector of inputs $\mathbf{x}_2 \subset \mathbf{X}$ and unobserved factors captured by an error term u_2:

(4) $Q_{2i} = \mathbf{x}_{2i}\boldsymbol{\beta}_2 + u_{2i}$.

If the error terms u_1 and u_2 are uncorrelated, those parameters can be estimated efficiently by estimating the OF and production function models separately. It is likely, though that unobserved factors such as pest disease, farmer's skill, and soil type affect both quality and quantity, in which case u_1 and u_2 will be correlated and it thus be more efficient to estimate the parameters of the quality and quantity models jointly.

To estimate the OF model and production function jointly, we assume that (u_1, u_2) has zero mean, bivariate normal distribution with var(u_1) = 1, var(u_2) = σ_2^2, and cov(u_1, u_2) = σ_{12}. Under joint normality of (u_1, u_2), we can write:

(5) $u_{1ic} = \lambda u_{2i} + \tilde{u}_{1ic}$

where $\lambda = \sigma_{12}/\sigma_2^2$. Because of joint normality, $\tilde{u}_1$ is also normally distributed with mean zero and variance given as $1 - \sigma_{12}/\sigma_2^2 = 1 - \rho^2$ where ρ = Corr(u_1, u_2).

To obtain the joint distribution of ($\mathbf{s}$, Q_2), recall that $f(\mathbf{s}, Q_2 \mid \mathbf{X}) = f(\mathbf{s} \mid Q_2, \mathbf{X}) \bullet f(Q_2 \mid \mathbf{X})$ (Wooldridge, 2010a, p.591). Since $Q_2 | \mathrm{X} \sim \mathrm{Normal}(\mathbf{x}_{2i}\boldsymbol{\beta}_2, \sigma_2^2)$, the density $f(Q_2 \mid \mathbf{X})$ is given as

(6) $f(Q_2 \mid \mathbf{X}) = \dfrac{1}{\sigma_2}\phi\left[\dfrac{Q_{2i} - \mathbf{x}_{2i}\boldsymbol{\beta}_2}{\sigma_2}\right]$

where ϕ denotes the standard normal probability density, i.e. $\phi(\mathrm{x}) = (2\pi)^{-0.5} \cdot \exp(-0.5x^2)$.

The density $f(\mathbf{s} \mid Q_2, \mathbf{X})$ can be expressed as equation (3), where p_g can be now rewritten as $p_g = \Pr(\mu_{g\text{-}1} \leq Q_{1ic} < \mu_g) = \Pr(\mu_{g\text{-}1} - \mathbf{x}_{1i}\boldsymbol{\beta}_1 - u_{2i} \leq \tilde{u}_{1ic} < \mu_g - \mathbf{x}_{1i}\boldsymbol{\beta}_1 - u_{2i})$ which yields

$$(7)\quad p_{gi} = \Phi\left(\frac{\mu_g - \mathbf{x}_{1i}\boldsymbol{\beta}_1 - \lambda u_{2i}}{\sqrt{\mathrm{Var}(\tilde{u}_{1ic})}}\right) - \Phi\left(\frac{\mu_{g-1} - \mathbf{x}_{1i}\boldsymbol{\beta}_1 - \lambda u_{2i}}{\sqrt{\mathrm{Var}(\tilde{u}_{1ic})}}\right)$$

$$= \Phi\left(\frac{\mu_g - \mathbf{x}_{1i}\boldsymbol{\beta}_1 - \rho/\sigma_2\left(Q_{2i} - \mathbf{x}_{2i}\boldsymbol{\beta}_2\right)}{(1-\rho^2)^{1/2}}\right) - \Phi\left(\frac{\mu_{g-1} - \mathbf{x}_{1i}\boldsymbol{\beta}_1 - \rho/\sigma_2\left(Q_{2i} - \mathbf{x}_{2i}\boldsymbol{\beta}_2\right)}{(1-\rho^2)^{1/2}}\right),$$

where we have used the fact $\lambda = \sigma_{12}/\sigma_2^2 = \rho/\sigma_2$.

Combining terms, the joint distribution is summarized as:

$$(8)\quad f(\mathbf{s}_i, Q_{2i} \mid \mathbf{X}_i) = \frac{C_i\,!}{\prod_{g=1}^{G} C_{gi}!} \cdot \prod_{g=1}^{G} p_{gi}^{C_{gi}} \cdot \frac{1}{\sigma_2}\phi\left[\frac{Q_{2i} - \mathbf{x}_{2i}\boldsymbol{\beta}_2}{\sigma_2}\right],$$

where we understand that p_g is given as equation (7). The log-likelihood can then be written (apart from terms not depending on the parameters[1]):

$$(9)\qquad \ln L_i = C_i \cdot \sum_{g=1}^{G} s_{gi} \log p_{gi} - \frac{1}{2}\log\left(\sigma_2^2\right) - \frac{1}{2} \cdot \frac{\left(Q_{2i} - \mathbf{x}_{2i}\boldsymbol{\beta}_2\right)^2}{\sigma_2^2}$$

Maximum likelihood estimators of the parameters $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ can be obtained by summing these individual likelihoods across all farms and maximizing the resulting expression with respect to the parameters. We call this estimator the “system ordered fractional (SOF)” model.

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[1] Assuming equal capacity of containers, C_i (the total number of containers) is proportional to Q_{2i} (production quantity) which depends on the parameters $\boldsymbol{\beta}_2$. However, since we are conditioning on Q_{2i}, we can treat C_i as exogenous.

Extension to Panel Data

Correlation between inputs that affect both the quantity and quality of output and unobserved factors that make up the error terms is likely to occur in many applications. For one thing, input choice may be correlated with time-invariant unobservables, such as soil quality and farm ability. Idiosyncratic shocks that vary by time and across farms, (e.g., pest pressure) may also be a source of correlation between regressors and the error terms. Panel data can be used to deal with unobserved heterogeneity in the former case. We discuss extension of the model to panel data in this section and treatment of idiosyncratic shocks in the next section.

Letting $t = 1, \ldots, T$ denote the time period and θ_{qi} denote unobserved time-invariant characteristics of farm i affecting quality ($q = 1$) and output ($q = 2$). The quality index and production function can be rewritten as $Q_{1itc} = \mathbf{x}_{1it}\boldsymbol{\beta}_1 + \theta_{1i} + e_{1itc}$, and $Q_{2it} = \mathbf{x}_{2it}\boldsymbol{\beta}_2 + \theta_{2i} + e_{2it}$ respectively.

As noted above, θ_q and $\mathbf{x}_q$ are likely to be correlated, in which case the random effects estimator is inconsistent. Because the model is nonlinear, the fixed effect estimator is also inconsistent due to the incidental parameters problem. As an alternative the correlated random effects (CRE) framework (Wooldridge 2010a, p.286) introduced by Mundlak (1978) can be used to control for unobserved heterogeneity. That model specifies a distribution of θ given $\mathbf{x}$ as

$$(10) \quad \theta_{qi} = \bar{\mathbf{x}}_{qi}\boldsymbol{\delta}_q + v_{qi},$$

where $\bar{\mathbf{x}}_{qi} \equiv T^{-1}\sum_{t=1}^{T}\mathbf{x}_{qit}$ is the vector of farmer-specific time averages of the covariates $\mathbf{x}_q$, and v_q is an error term with mean-zero normal distribution that is independent of $\mathbf{x}_q$. Unlike fixed effect model, CRE imposes a specific functional relationship between θ and $\mathbf{x}$, but it has been shown that when model is linear, CRE estimates (adding the time averages of the covariates and applying either pooled OLS or random effects) are identical to the fixed effects (within) estimates (Mundlak 1978; Wooldridge 2010b).

Using the CRE framework, the quality index can be rewritten as $Q_{1itc} = \mathbf{x}_{1it}\boldsymbol{\beta}_1 + \bar{\mathbf{x}}_{1i}\boldsymbol{\delta}_1 + u_{1itc}$, where $u_{1itc} \equiv v_{1i} + e_{1itc}$, assumed to be normally distributed as before with a variance normalized to unity. The production function can similarly be expressed as $Q_{2it} = \mathbf{x}_{2it}\boldsymbol{\beta}_2 + \bar{\mathbf{x}}_{2i}\boldsymbol{\delta}_2 + u_{2it}$, where $u_{2it} = v_{2i} + e_{2it}$. Assuming joint normality for (u_1, u_2), maximum likelihood estimators of the parameters $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ can be obtained as discussed earlier, with regressors $\mathbf{x}_{qi}$ replaced by $(\mathbf{x}_{qit}, \bar{\mathbf{x}}_{qi})$, i.e., with time averages of the covariates added to the set of regressors.

Extension to Endogenous Regressors

Idiosyncratic errors correlated with the regressors can be handled using the control function approach (Wooldridge 2010a, p. 586), provided that valid instruments are available. Let $\mathbf{Y}_{it}$ ($1\times K$ vector) denote the vector of endogenous variables appearing anywhere in the system. In this case, the quality index and production function can be rewritten as $Q_{1itc} = \mathbf{y}_{1it}\boldsymbol{\alpha}_1 + \mathbf{x}_{1it}\boldsymbol{\beta}_1 + \theta_{1i} + e_{1itc}$ and $Q_{2it} = \mathbf{y}_{2it}\boldsymbol{\alpha}_2 + \mathbf{x}_{2it}\boldsymbol{\beta}_2 + \theta_{2i} + e_{2it}$, respectively, where $\mathbf{y}_{qit} = (y_{q1it}, y_{q2it},...) \subset \mathbf{Y}_{it}$. We have in addition to the quality and quantity equations reduced-form equations for the endogenous regressors:

(11) $y_{qkit} = \mathbf{Z}_{it}\boldsymbol{\gamma}_{qk} + \xi_{qki} + w_{qkit}$ $(k = 1,..., K_q)$

where $\mathbf{Z} = (\mathbf{z}, \mathbf{x}_1, \mathbf{x}_2)$, **z** is a vector of excluded instrumental variables, ξ denotes unobserved effects, and *w* is a vector of white noise errors. Assume that *e* and *w* are uncorrelated with **Z** and **x**'s but that *e* and *w* are correlated (so that *e* and **y** are correlated), specifically, that they are jointly normally distributed with a zero mean and constant covariance matrix. Then *e* can be decomposed into a mean conditional on *w* and deviations around this mean:

$$(12)\quad e_q = E\left[e_q \middle| w_{q1},..., w_{qK_q} \right] + \tilde{e}_q = \sum_{k=1}^{K_q} \tau_{qk} w_{qk} + \tilde{e}_q \equiv \mathbf{w}_q \boldsymbol{\tau}_q + \tilde{e}_q .$$

The quality index and production function can then be rewritten as $Q_{1itc} = \mathbf{y}_{1it}\boldsymbol{\alpha}_1 + \mathbf{x}_{1it}\boldsymbol{\beta}_1 + \theta_{1i} + \mathbf{w}_{1it}\boldsymbol{\tau}_1 + \tilde{e}_{1itc}$ and $Q_{2it} = \mathbf{y}_{2it}\boldsymbol{\alpha}_2 + \mathbf{x}_{2it}\boldsymbol{\beta}_2 + \theta_{2i} + \mathbf{w}_{2it}\boldsymbol{\tau}_2 + \tilde{e}_{2it}$ respectively. By construction, $\tilde{e}_q$ is uncorrelated with **w** and is therefore uncorrelated with **y**, so that using estimates of **w** as additional covariates can be used to control for potential endogeneity bias.

The parameters of the model can be estimated in this case by a two-stage procedure. In the first stage, equation (11) is estimated to obtain estimates of **w**. In the second stage, the estimated residuals **w** are added as explanatory variables in the likelihood function. Because the second stage uses an estimate of **w** from the first stage, as opposed to the true **w**, the asymptotic sampling variance of the second-stage estimator needs to take this extra source of variation into account, which can be accomplished by bootstrapping (Petrin and Train 2010).

Estimating Quality versus Quantity Effects in Japanese Wheat Production

As discussed in Kawasaki and Lichtenberg (2014), under the terms of the Japanese Agricultural

Products Inspection Law of 1951, wheat in Japan is graded into one of three categories. The highest two grades are reserved for food uses while the lowest grade is used only for animal feed. The determination of grade follows a procedure like the one described in specifying the SOF model. Wheat is packed into multiple containers of uniform size at harvest; each container is then sampled by a government inspector and assigned a grade that depends on criteria that include kernel size, specific weight, mold damage, and cleanliness, all of which can be affected by chemical use. Fertilizer application can affect kernel size and specific. Weed control by herbicides, hand weeding, and hand sorting at harvest can affect cleanliness. Fungicide applications and field drainage can affect diseases such as ergot, smut, scab, and mold. Field drainage can also influence pre-harvest sprouting.

Data

We use the same confidential farm-level data for the period 1995– 2006 as Kawasaki and Lichtenberg (2014). These data are obtained from a multistage stratified random sample of wheat farms in Japan surveyed annually by the Ministry of Agriculture, Forestry and Fisheries (MAFF). MAFF uses information from the most recent census to determine the number of farms of each size to be sampled in each prefecture, then draws farms in each size category at random on an annual basis. The result is an unbalanced panel with a total of 1,342 farms. Over 500 of these farms were sampled only once; this subsample is used only in a model in which all regressors are assumed exogenous. Of the remaining farms, over a third was sampled in two years, roughly a quarter was sampled in three years, and another tenth in four years, with the remainder appearing 5-11 times in the data set. Some of these farms with multiple observations appear in the sample in consecutive years while others appears non-consecutively (see table 2 of Kawasaki and

Lichtenberg (2014) for details).

The data contain detailed information about the area of wheat grown (in hectares), about the area planted to each of the four major Japanese wheat varieties (*Chihoku*, *Norin 61*, *Shirogane*, and *Hokushin*) in addition to other, less commonly used varieties; about inputs; and about the weight and value of wheat harvested by grade. Inputs like fertilizer, herbicides, insecticides, and fungicides are measured in terms of expenditures per hectare. Labor is reported in hours per hectare. The stock of machinery is measured by the total value of agricultural machinery per hectare. Farmers also report the rental value of the land operated and the wage paid for hired labor.

In Japan, regional farmers unions and millers negotiate contracts specifying prices for wheat of different grades during the summer before wheat is planted, so that wheat prices are set prior to planting and cultivation decisions. Additionally, Japan imports almost all the wheat it consumes, so price levels are determined mainly in international markets. Each farm in the survey sample reported the price received for wheat of each grade produced. However, many farms did not produce one or more grades of wheat in any given year. Only about a tenth of the sample reported production of positive amounts of all three grades. Almost a third of the observations reported production of high grade wheat only, an eighth reported medium grade only, and a tenth reported high and medium grade (i.e., no low grade) only. When a farm did not produce wheat of a given grade, we use the sample average price received in that year for grades in the city in which the farm is located. There was no variation in reported prices received by farmers within any city, so this substitution does not introduce any error. The consumer price index (2005=100) is used to convert all prices, expenditures and values to real terms.

Both the quality and quantity of wheat are affected by weather conditions (notably temperature and humidity during the growing season). We use data on temperature, precipitation, and snowfall to control for weather conditions during the growing season; details can be found in Kawasaki and Lichtenberg (2014).

Finally, we control for features of the landscape in which the farm is located. Wheat may be planted in drained paddy (lowland) areas or in upland areas; the latter tend to be drier and thus less prone to disease pressure but are also usually less fertile. Topography of farms falls into one of three categories: (1) flat agricultural, (2) hilly, and (3) mountainous. Some wheat is also grown in urban locations, which are categorized as a separate kind of topography. Flat agricultural land is best suited for crop production while mountainous locations are least.

Definitions and summary statistics of all variables used here are shown in table 2.

Model Specification and Estimation

We specify the both the latent quality index and quantity as quadratic functions of agricultural chemicals, labor, machinery, wheat planted area, wheat varieties grown, weather conditions, topography, and price differentials between grades. We express quantity in terms of the natural log of yield (in kilograms per hectare) to ensure that the errors are (at least asymptotically) normal. We exclude cross-effects between inputs.

We expect pesticides, fertilizer, labor, and machinery to have positive effects on both the quantity and quality of wheat grown. Fertilizers increase yield, in part by increasing grain size and weight, both of which are determinants of grade. Fungicides and insecticides reduce damage from diseases and insects, respectively. Herbicides and labor increase yields by removing weed competition as well as lowering contamination from weed seeds. Wheat varieties differ in terms of yield and factors affecting quality such as disease resistance, grain size, and weight. Both yield and quality are also likely to be influenced by weather conditions. Upland share and topography have well-known effects on yield; there is less a priori information about their effects on quality. Price differentials between high and medium quality wheat and between medium and low quality wheat are also included to control for unobserved input choices and farmer effort levels. We use price differentials rather than absolute prices because higher price differentials change the relative profitability of different grades.

Upland share, topography, and weather are treated as exogenous, as are wheat price differentials—the latter because wheat prices are finalized prior to planting and are heavily influenced by world market prices. Pesticides and fertilizer, by contrast, are treated as potentially endogenous because usage levels might well be correlated with an idiosyncratic error like soil moisture and disease pressure. We treat labor, machinery, planted wheat area, and varietal choices as uncorrelated with unobservables.

Our main specification uses as instruments the wage paid for each farm's labor, each farm's land rent, indexes of prices of pesticide, fertilizer, seed, energy, and machinery that vary across prefecture and year. Each farm's wage rate was calculated as a weighted average of hired labor, whose wage was reported by each farm, and family labor, which was assumed to equal the average wage paid by small businesses in the same prefecture, as reported by the Ministry of Health, Labor and Welfare. Each farm's land rent was calculated as a weighted average of rent paid on rented land and the rent for own land, which was evaluated using the market rent for farmland in the same village (or city, if village rent was not available) with the same soil fertility and land type. Price indexes for the remaining inputs are based on monthly reports from the principal retailers in each prefecture. We use the price index for the year in which the crop was harvested because wheat in Japan is planted in the fall and harvested the following summer.

As a robustness check, we estimated the parameters using as instruments the average input usage (fungicide, insecticides, herbicides, fertilizer, labor, and wheat planted area) by neighboring farmers during the preceding year.[2] This procedure requires dropping observations from the first year of the sample (but not the first year in which every farm is observed).

We use the control function approach to estimate the parameters of the quality and quantity models. The first stage regressions of these models include all of the exogenous regressors in addition to the instruments listed above, and are estimated using linear models with farm-specific fixed effects (within) estimators. We used Mundlak's correlated random effects approach (by including farm-specific averages of all instruments and exogenous variables) in the second stage to control for the potential correlation between regressors and time-invariant unobserved effects. All specifications include year and region dummy variables to control for year- and region-specific unobservables. Standard errors are clustered by farm using bootstrapping with 500 replications.

Estimation Results

The estimated coefficients of the first stage regressions of chemical use on input prices and are

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[2] In cases where there are no more than two farmers in the same city, the average share of those varieties planted by other farmers in the same prefecture was used instead. If prefecture level averages were unavailable, regional averages were used.

shown in table 3. Our model is largely the same as that of Kawasaki and Lichtenberg (2014), differing only in featuring both linear and quadratic terms of all variables included in the second stage system ordered fractional model. It is thus no surprise that the first stage estimates of fit the data reasonably well and that input demands are downward sloping in price. The input prices indexes we use are not strong instruments for fungicides, insecticides, herbicides, or fertilizer, as indicated by *F*-statistics less than 10, the rule of thumb suggested by Staiger and Stock (1997). As Kawasaki and Lichtenberg (2014) show, though, the OF estimator performs well even with weak instruments.[3]

While our instruments may not be strong, the coefficients of the first stage residuals from the second stage regression provide only weak confirmation of potential correlation between per hectare pesticide and fertilizer expenditures and unobserved factors influencing both the latent quality index and yield: As can be seen from table 4, which contains the estimated coefficients of the second stage regression, the hypothesis that the coefficients of all first stage residuals are all zero cannot be rejected at any reasonably significance level. These considerations suggest that our estimates of the effects of pesticides and fertilizer are not affected by endogeneity bias to any appreciable degree.

As the estimates in table 4 indicate, both the latent quality index and the log of yield are increasing in fungicide and fertilizer use but are unaffected by insecticide and herbicide use. These results attest to the importance of kernel size, weight, and disease damage in Japanese wheat grading as well as to the importance of reductions in disease losses in damage abatement.

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[3] The estimated coefficients of the first stage regressions on neighbors' lagged use of all inputs are shown in Table A1. The estimated coefficients of variables from the second stage regression are largely the same as in the base model, indicating robustness with respect to instrument choice.

Among varieties, we find that the latent quality index is increasing in the share of land planted to the *Hokushin* variety, the newest variety used, which has better disease resistance and grain with a higher specific weight. Both the quality and quantity of wheat depend on location and climate. Farms with a higher share of wheat planted on upland areas have a lower latent quality index and lower yields. Temperature and precipitation in winter and spring clearly influence both quality and quantity as well.

Quality versus Quantity Effects

Both the yield and quality models are highly nonlinear, so the effects of inputs, location, weather, and other factors are best assessed in terms of their marginal effects rather than their estimated coefficients. In order to compare quality and quantity effects, we use the estimated parameters of the SOF model to calculate the marginal contributions of pesticides, fertilizer, and labor to overall output value via changes in the quality and quantity of output. Letting π_i denote output value per hectare on farm i and p output price, output value can be defined as $\pi_i = [\Sigma_g p_g s_{gi}(\boldsymbol{X_i})] Q_{2i}(\boldsymbol{X_i})$. The marginal contribution of input j used on farm i to output value on farm i is thus:

$$(11) \qquad \frac{\partial \pi_i}{\partial X_{ij}} = \left[\sum_g p_g \frac{\partial s_{gi}}{\partial X_{ij}} \right] \cdot Q_{2i}(\mathbf{X}_i) + \left[\sum_g p_g s_{gi}(\mathbf{X}_i) \right] \cdot \frac{\partial Q_{2i}}{\partial X_{ij}}$$

The first term is the marginal contribution of the input in terms of quality while the second term is the marginal contribution in terms of quality, both measured in terms of overall output value. We calculate the overall marginal effects and its quality and quantity components and then average all three across all observations.

These estimates of marginal effects indicate that fungicides, fertilizer, location, and climate have statistically significant effects on quality while fungicides, fertilizer, variety, location, and climate have statistically significant effects on yield (table 5).

Pesticides and Fertilizer

Among chemicals, fungicides and fertilizer have marginal effects that are statistically significantly different from zero while insecticides and herbicides do not. Fungicides in particular make one of the largest marginal contributions to wheat crop value, underscoring the importance of disease control in wheat production. The marginal contribution of fungicides to quality is about a fifth the size of its marginal contribution to quantity. Fertilizer's marginal contributions to crop value are much smaller than those of fungicides. Its marginal contribution to quality accounts for a much larger share of its overall effect, attesting to the importance of kernel size and weight in Japanese wheat grading.

It is not surprising that neither insecticide use nor herbicide use has no statistically discernible effect on wheat production. Due to the low incidence of insect problems, insecticide use is not at all prevalent in Japanese wheat production. The incidence of weed problems appears to be similarly low. The marginal contribution of herbicide use to quality is negligible in magnitude as well as statistically indiscernible from zero, suggesting strongly that herbicide use has no effect on wheat quality. Intuitively, the density at which wheat is grown is high enough that the crop crowds out weeds.

Crop Varieties

The shares of land planted to the *Chihoku*, *Norin61*, and *Shirogane* varieties are associated with both yields and quality that are significantly lower than other, less widely used varieties. The *Norin61* and *Shirogane* varieties are quite old (having been introduced in 1943 and 1974, respectively) and are planted mainly in middle and southern Japan. *Shirogane* produces grain with a higher specific weight but is more prone to sprouting than *Norin61*. *Hokushin*, the newest variety (introduced 1995), has better disease resistance and produces grain with a higher specific weight than *Chihoku* (introduced 1981); our results provide some weak evidence that *Hokushin* produces slightly higher quality wheat at a cost of slightly lower yield.

Climate

Our estimates indicate that higher winter temperatures are associated with both higher wheat quality and higher wheat yields, while greater snowfall, higher spring temperatures and higher spring precipitation are associated with lower wheat quality and yield. Greater winter precipitation is associated with higher wheat quality but lower yields. The Japan Meteorological Agency (2013) currently projects that by the end of this century, average winter temperature will increase by 3.2 degrees Celsius, average winter precipitation will increase by 0.8 mm, average snowfall will decrease by 0.35 cm, average spring temperature will increase by 2.9 degrees Celsius, and average spring precipitation will increase by 6.3 mm.

As a rough estimate of the overall effect of climate change on Japanese wheat production, assume that wheat prices remain unchanged—a plausible assumption in light of the fact that Japan imports most of its wheat. Our estimated coefficients imply that currently projected changes in climate would increase Japanese wheat quality in value terms by about 316 yen but decrease wheat yields in value terms by nearly 5 times as much, almost 1500 yen per hectare (table 6). These figures suggest strongly that a changed climate would reduce Japanese wheat yields far more than could be offset by any improvements in quality.

Conclusion

While the use of pesticides to protect product quality is widely recognized, there is little empirical evidence about the extent to which they do so—and even less evidence about the importance of quality protection relative to yield protection. We investigate the relative magnitudes of the quality and quantity effects of pesticides in the context of Japanese wheat production. To do so, we extend the ordered fractional model of Kawasaki and Lichtenberg (2014) for estimating the determinants of grade shares by incorporating it into a simultaneous equation system in which quality and quantity effects are estimated jointly, which allows more efficient estimation and hypothesis testing. Correlated random effects are used to control for unobserved time-invariant heterogeneity. Pesticides and fertilizer are treated as endogenous. The model is estimated in two stages using a control function approach to correct for endogeneity, with input prices or used as instruments in the first stage regressions. We obtain the same results using neighbors' lagged input uses as instruments. We use the estimated parameters of the model to calculate the marginal contributions of agricultural chemicals, varietal choice, and climate to overall output value via changes in the quality and quantity of output.

The estimated parameters of these models indicate that fungicides increase both the quality and quantity of output. The quality effects of fungicides are substantial, accounting for about 18% of the contribution to overall revenue. Put another way, the marginal contribution of fungicides to wheat revenue by improving its quality is on the order of 21% of the marginal contribution due to yield increases. This finding highlights the key role played by disease control in wheat production and thus the critical importance of addressing rising threats of various diseases (e.g. new highly virulent stem rust races and likely increases in fusarium ear blight and other wheat diseases) that are likely to become even more dangerous with climate change. Insecticides and herbicides, in contrast, have no statistically significant effect on either quality or yield.

Fertilizer also has a statistically significant effect on both quality and yield. Its effects on crop value are much smaller at the margin than those of fungicides. The quality effect of fertilizer is larger than that of fungicides relative to the quantity effect, though, amounting to almost 45% of the yield effect—a result that highlights the importance of kernel size and weight in wheat grade determination.

Overall, our results demonstrate the importance of including quality effects in estimating the productivity of agricultural chemicals. In our case, ignoring quality effects leads to a substantial underestimate of the marginal productivities of fungicides and fertilizers. Benefit cost analyses that ignore these quality effects in evaluating the tradeoffs between environmental spillovers from these chemicals against agricultural productivity will thus be biased. In our case, that bias appears to be quite substantial.

Like Kawasaki and Lichtenberg (2014), we find that projected climate changes will likely be associated with higher wheat quality. But any improvements in wheat quality are likely to be swamped by reductions in Japanese wheat yields. Thus, climate change is likely to have an unambiguously negative effect on Japanese wheat production.

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Table 1. Grading Standards for Wheat in Japan (1995-2006)

Characteristic	High grade (*1tou*)	Medium grade (*2 tou*)	Low grade (*kikakugai*)
Minimum allowable levels of:			
Specific weight (gram/liter)	760	710	-
Kernel size > 2 mm (%)	75	60	-
Appearance (bran layer thickness, maturity, hardness, uniformity, shape, and gloss)	Conformity with photo of high grade sample	Conformity with photo of medium grade sample	-
Maximum allowable levels of:			
Moisture (%)	12.5	12.5	-
Damaged wheat, non-wheat, non-grain (%)			
Total	5.0	15.0	50.0
Non-wheat grain	0.5	1.0	-
Non-grain			-
Ergot infected	0.0	0.0	-
Smut infected	0.1	0.1	-
Other non-grains	0.4	0.6	
Other conditions			-
Scab infected (%)	0.0 (after 2003)	0.0 (after 2003)	-
	0.1 (before 2002)	0.1 (before 2002)	
Black mold infected (%)	5.0	5.0	-
Sprouted wheat (%)	2.0	2.0	-
Soil and sand (%)	0.0	0.0	
Smell	none	none	
Source: Kawasaki and Lichtenberg (2014), table 1.			

Table 2. Variable Definitions and Summary Statistics

Variable	Definition	Mean	Standard Deviation
High Grade	Output share of high grade wheat	0.650	0.422
Medium Grade	Output share of medium grade wheat	0.268	0.390
Low Grade	Output share of low grade wheat	0.082	0.190
Fungicide Expenditure	Fungicide expenditure (10000 Yen/ha)	0.989	1.389
Insecticide Expenditure	Insecticide expenditure (10000 Yen/ha)	0.087	0.230
Herbicide Expenditure	Herbicide expenditure (10000 Yen/ha)	1.758	1.124
Fertilizer Expenditure	Fertilizer expenditure (10000 Yen/ha)	5.975	2.755
Labor Time	Labor time (100 hour/ha)	0.906	0.737
Wheat Planted Area	Wheat planted area (0.01 ha)	343.4	467.5
Chihoku Share	Share planted to *Chihoku* variety	0.044	0.198
Norin61 Share	Share planted to *Norin61* variety	0.317	0.448
Shirogane Share	Share planted to *Shirogane* variety	0.149	0.347
Hokushin Share	Share planted to *Hokushin* variety	0.179	0.377
Price Differential (Medium/Low)	Price differential between medium and low grade wheat (100 Yen/kg)	1.066	0.146
Price Differential (High/Medium)	Price differential between high and medium grade wheat (100 Yen/kg)	0.191	0.066
Agricultural Machinery	Stock of agricultural machinery (100000 Yen)	0.043	0.048
Upland Share	Share planted in upland plot	0.244	0.414
Farm Area	Total farmland (0.01 ha)	966.4	1169.2
Hilly Location	1 if farm located in hilly location	0.138	0.345
Mountainous Location	1 if farm located in mountainous location	0.008	0.089
Urban Location	1 if farm located in urban location	0.220	0.414
Winter Temperature	Average daily temperature October through March (°C)	6.297	4.648
Winter Precipitation	Average daily precipitation October through March (mm)	2.387	0.950
Winter Snowfall	Average daily snowfall October through March (cm)	0.954	1.517
Spring Temperature	Average daily temperature April through June (°C)	16.140	3.710
Spring Precipitation	Average daily precipitation April through June (mm)	4.588	2.622
Labor Wage	Labor wage (100 Yen/hour)	15.788	2.014
Pesticide Price Index	Price index of pesticides (Year 2000 = 1)	0.962	0.037
Fertilizer Price Index	Price index of fetilizer (Year 2000 = 1)	0.982	0.050
Seed Price Index	Price index of seeds (Year 2000 = 1)	0.969	0.049
Material Price Index	Price index of materials (Year 2000 = 1)	0.973	0.037
Energy Price Index	Price index of energy (Year 2000 = 1)	1.027	0.133
Machinery Price Index	Price index of agricultural machines (Year 2000 = 1)	0.965	0.032
Land Rent	Land rent (10000 Yen/ha)	10.523	5.778

Table 3. Estimated Coefficients of First Stage Chemical Use Regressions

Variable	**Dependent Variable: Per-Hectare Expenditures on**			
	Fungicide	**Insecticide**	**Herbicide**	**Fertilizer**
Labor Wage	0.0194 [2.40]**	0.0048 [2.32]**	0.0103 [0.72]	0.0384 [1.20]
Pesticide Price Index	-0.923 [-2.06]**	0.111 [0.53]	-0.307 [-0.26]	3.09 [1.56]
Fertilizer Price Index	-1.22 [-1.92]*	-0.166 [-0.93]	-2.01 [-1.95]*	-4.82 [-2.38]**
Seed Price Index	-1.28 [-3.84]***	-0.006075 [-0.09]	1.61 [1.24]	-5.21 [-3.54]***
Energy Price Index	0.536 [1.80]*	-0.005 [-0.07]	-1.35 [-2.75]***	-0.404 [-0.37]
Machinery Price Index	0.943 [1.39]	-0.100 [-0.52]	2.390 [1.80]*	2.780 [1.10]
Land Rent	0.00066 [0.23]	0.00218 [1.98]**	0.00572 [1.23]	-0.00225 [-0.25]
Labor Time	0.289 [2.96]***	0.02011 [1.15]	0.628 [4.66]***	0.855 [3.41]***
Labor Time Squared	-0.02596 [-2.54]**	-0.0016173 [-0.86]	-0.04493 [-2.33]**	-0.03803 [-1.32]
Wheat Planted Area	-0.0278 [-1.72]*	-0.0018976 [-0.37]	0.00559 [0.22]	-0.04502 [-0.90]
Wheat Planted Area Squared	3.06E-04 [1.80]*	8.64E-06 [0.16]	-0.0003648 [-1.40]	0.0004172 [0.82]
Chihoku Share	0.02795 [0.09]	-0.0041014 [-0.05]	-0.08225 [-0.38]	-1.31 [-1.98]**
Norin61 Share	-0.02846 [-0.53]	0.0050769 [0.59]	0.08892 [0.68]	-0.533 [-2.94]***
Shirogane Share	-0.14 [-2.01]**	-0.0057943 [-0.33]	-0.06312 [-0.45]	0.325 [1.46]
Hokushin Share	-0.217 [-0.74]	-0.11 [-1.47]	0.221 [1.06]	-0.579 [-0.83]
Price Differential (Medium/Low)	0.258 [2.41]**	0.0018003 [0.06]	0.0090851 [0.05]	1.65 [3.36]***
Price Differential (High/Medium)	-0.09992 [-0.44]	-0.07061 [-1.03]	-0.106 [-0.29]	-0.379 [-0.45]
Agricultural Machinery	0.824 [2.69]***	0.01778 [0.27]	0.549 [0.91]	1.76 [1.55]
Upland Share	0.182 [1.26]	0.112 [2.07]**	-0.0429 [-0.19]	0.716 [1.98]**

Farm Area	-0.003103 [-0.66]	-0.0004017 [-0.28]	0.0041987 [0.54]	0.009453 [0.50]
Winter Temperature	0.02718 [0.55]	0.03098 [2.54]**	0.04435 [0.97]	0.175 [1.21]
Winter Temperature Squared	-5.46E-05 [-0.02]	-0.000962 [-1.26]	0.0010396 [0.30]	-0.0054399 [-0.54]
Winter Precipitation	-0.118 [-2.46]**	0.0078295 [0.56]	-0.109 [-1.03]	0.05897 [0.41]
Winter Precipitation Squared	0.0070364 [1.22]	-0.0015078 [-0.85]	0.01088 [0.61]	-0.02847 [-1.41]
Winter Snowfall	0.07672 [0.98]	0.04674 [2.45]**	0.173 [1.81]*	-0.339 [-1.52]
Winter Snowfall Squared	-0.0053898 [-0.68]	-0.0051649 [-2.59]***	-0.01213 [-1.21]	0.03695 [1.57]
Spring Temperature	0.03161 [0.33]	0.06884 [2.19]**	0.03931 [0.42]	0.288 [1.38]
Spring Temperature Squared	0.0001043 [0.04]	-0.0013454 [-1.61]	0.0018451 [0.61]	-0.0052921 [-0.78]
Spring Precipitation	0.0039422 [0.16]	0.0059638 [0.94]	0.02172 [0.63]	-0.02245 [-0.33]
Spring Precipitation Squared	6.24E-05 [0.04]	-0.0004412 [-1.18]	-0.0014812 [-0.63]	0.0040916 [0.99]
Hilly Location	0.05381 [0.78]	0.008741 [0.50]	-0.03256 [-0.43]	-0.461 [-1.89]*
Mountainous Location	-0.555 [-2.22]**	-0.07466 [-1.96]*	0.843 [2.60]***	0.343 [0.23]
Urban Location	0.05864 [1.39]	0.0009116 [0.08]	0.04674 [0.64]	-0.136 [-0.77]
R^2	0.713	0.259	0.184	0.227
Observations	3979			
Test of weak instruments (H_0: Coefficients of all instruments equal zero)				
F-statistic (p-value)	5.251 (0.000)	1.744 (0.094)	2.359 (0.021)	2.448 (0.017)
***, **, * denote significantly different from zero at 1%, 5%, and 10% significance levels, respectively.				

Table 4. Estimated Coefficients of the System Ordered Fractional Model

Variable	Latent Quality Index		Ln Yield	
	Coefficient	Standard Error	Coefficient	Standard Error
Fungicide Expenditure	0.201	0.084**	0.152	0.047***
Fungicide Expenditure Squared	-0.011	0.009	-0.007	0.004*
Insecticide Expenditure	-0.326	0.460	-0.056	0.352
Insecticide Expenditure Squared	-0.049	0.086	0.019	0.038
Herbicide Expenditure	-0.048	0.082	-0.034	0.036
Herbicide Expenditure Squared	0.016	0.012	0.001	0.005
Fertilizer Expenditure	0.051	0.027	0.022	0.010**
Fertilizer Expenditure Squared	0.000	0.001*	0.000	0.001
Labor Time	-0.237	0.286	0.089	0.116
Labor Time Squared	0.051	0.052	-0.002	0.023
Wheat Planted Area	-0.033	0.030	-0.020	0.024
Wheat Planted Area Squared	0.000	0.001	0.000	0.001
Chihoku share	-0.192	0.241	-0.405	0.120***
Norin61 share	-0.128	0.164	-0.189	0.058***
Shirogane share	-0.203	0.229	-0.150	0.057***
Hokushin share	0.048	0.241	-0.009	0.128
Price Differential (Medium/Low)	0.363	0.280	0.080	0.119
Price Differential (High/Medium)	0.519	0.497	0.077	0.216
Agricultural Machinery	0.526	1.118	0.292	0.323
Upland Share	-0.862	0.221***	-0.324	0.106***
Farm Area	0.001	0.010	0.006	0.004
Winter Temperature	0.305	0.062***	0.099	0.031***
Winter Temperature Squared	0.017	0.005***	0.004	0.002***
Winter Precipitation	0.338	0.156**	-0.080	0.056
Winter Precipitation Squared	-0.016	0.025	0.006	0.009
Winter Snowfall	-0.101	0.112	-0.032	0.058
Winter Snowfall Squared	0.018	0.015	0.003	0.009
Spring Temperature	0.687	0.130***	0.307	0.067***
Spring Temperature Squared	-0.031	0.004***	-0.016	0.002***
Spring Precipitation	-0.073	0.052	-0.038	0.018**
Spring Precipitation Squared	-0.006	0.003*	0.000	0.001
Hilly Location	-0.070	0.084	0.038	0.044
Mountainous Location	0.188	0.278	0.127	0.108
Urban Location	0.114	0.089	0.047	0.029
First-Stage Residuals				

Fungicide Expenditure		-0.125	0.069*	-0.081	0.036**
Insecticide Expenditure		0.617	0.499	0.101	0.369
Herbicide Expenditure		-0.050	0.079	0.027	0.030
Fertilizer Expenditure		-0.049	0.029*	0.002	0.015
Threshold parameters					
	μ_1	-2.191	1.503		
	m_2	-0.175	0.066		
Correlation between quality and quantity errors					
	ρ_0	0.443	0.044		
Test of endogeneity (H0: First stage residuals of all potentially endogenous variables equal zero)					
	F-statistic	1.63		1.66	
	(p-value)	0.16		0.16	
Test of correlated random effects (H0: Farmer-specific averages of all exogenous variables equal zero)					
	F-statistic	6.92		4.26	
	(p-value)	0.00		0.00	
	Observations	3979			
	Log likelihood	-7480.69			
***, **, * denote significantly different from zero at 1%, 5%, and 10% significance levels, respectively.					

Table 5: Marginal Contributions of Inputs to Wheat Value due to Quality, Yield and Overall

Variable	**Quality Effect**		**Quantity Effect**		**Overall Effect**		**Quality:Quantity Effect Ratio**
	Estimate	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**	
Fungicide Expenditure	1.426	0.573**	6.679	1.979***	8.105	2.386***	0.213
Insecticide Expenditure	-2.729	3.604	-2.574	17.097	-5.303	18.498	1.060
Herbicide Expenditure	0.072	0.477	-1.488	1.184	-1.416	1.535	-0.048
Fertilizer Expenditure	0.375	0.138***	0.851	0.356***	1.226	0.438***	0.441
Labor Hours	-1.193	1.665	4.162	4.058	2.968	5.162	-0.287
Wheat Planted Area	-0.253	0.208	-0.923	0.983	-1.176	1.145	0.274
Chihoku Share	-1.558	1.930	-19.735	5.831***	-21.293	7.002***	0.079
Norin61 Share	-1.038	1.299	-9.207	2.806***	-10.245	3.482***	0.113
Shirogane Share	-1.642	1.836	-7.297	2.757***	-8.939	3.750**	0.225
Hokushin Share	0.388	1.908	-0.444	6.215	-0.057	7.232	-0.872
Price Differential (Medium/Low)	2.942	2.236	3.879	5.807	6.821	7.354	0.758
Price Differential (High/Medium)	4.205	3.989	3.773	10.482	7.978	11.997	1.114
Agricultural Machinery	4.264	8.979	14.221	15.722	18.485	20.075	0.300
Upland Share	-6.983	1.775***	-15.788	5.120***	-22.771	6.048***	0.442
Farm Area	0.009	0.082	0.288	0.199	0.297	0.242	0.031
Winter Temperature	3.970	0.613***	7.183	1.809***	11.153	2.212***	0.553
Winter Precipitation	2.138	0.449***	-2.562	1.071**	-0.424	1.344	-0.835
Winter Snowfall	-0.484	0.656	-1.257	2.158	-1.741	2.469	0.385
Spring Temperature	-2.159	0.513***	-9.416	1.446***	-11.575	1.735***	0.229
Spring Precipitation	-1.008	0.209***	-1.799	0.385***	-2.807	0.482***	0.560

***, **, * denote significantly different from zero at 1%, 5%, and 10% significance levels, respectively.

Table 6. Impact of Climate Change on Japanese Wheat Quality and Quantity

	Projected Change		Marginal effect on revenue through		Change in revenue (100 yen/ha)		
			Quality	Quantity	Quality Effect	Quantity Effect	Total
Winter Temperature	3.5	°C	3.97	7.183	13.90	25.14	39.04
Winter Precipitation	0.8	mm	2.138	-2.562	1.71	-2.05	-0.34
Winter Snowfall	-0.35	mm	-0.484	-1.257	0.17	0.44	0.61
Spring Temperature	2.9	°C	-2.159	-9.416	-6.26	-27.31	-33.57
Spring Precipitation	6.3	mm	-1.008	-1.799	-6.35	-11.33	-17.68
Total					3.16	-15.11	-11.94

Table A1. Estimated Coefficients of First Stage Chemical Use Regressions, Alternative Instrument Specification

Variable	Dependent Variable: Per-Hectare Expenditures on			
	Fungicide	**Insecticide**	**Herbicide**	**Fertilizer**
Lagged Neighbors' Fungicide Expenditure	0.259 [4.19]***	-0.01949 [-1.42]	0.0129 [0.27]	0.191 [1.67]*
Lagged Neighbors' Insecticide Expenditure	0.06052 [0.33]	0.216 [2.66]***	-0.138 [-0.57]	0.532 [1.21]
Lagged Neighbors' Herbicide Expenditure	0.059 [2.44]**	-0.003 [-0.48]	0.190 [3.14]***	-0.019 [-0.23]
Lagged Neighbors' Fertilizer Expenditure	0.022 [1.58]	0.007 [1.84]*	0.045 [2.15]**	0.197 [4.60]***
Labor Time	0.309 [3.03]***	0.01155 [0.63]	0.62 [4.14]***	0.946 [3.75]***
Labor Time Squared	-0.02724 [-2.75]***	-0.000891 [-0.49]	-0.04268 [-2.11]**	-0.04949 [-1.68]*
Wheat Planted Area	-0.03234 [-1.99]**	-0.004223 [-0.84]	0.0049693 [0.17]	-0.04169 [-0.84]
Wheat Planted Area Squared	3.58E-04 [2.07]**	2.84E-05 [0.54]	-0.00033 [-1.11]	0.0004173 [0.79]
Chihoku Share	0.143 [0.39]	0.02027 [0.25]	0.09153 [0.37]	-1.52 [-2.00]**
Norin61 Share	-0.03305 [-0.54]	0.0085899 [0.98]	0.07571 [0.53]	-0.513 [-2.64]***
Shirogane Share	-0.0566 [-0.75]	-0.005099 [-0.24]	-0.01632 [-0.09]	0.39 [1.26]
Hokushin Share	-0.01995 [-0.06]	-0.04793 [-0.62]	0.137 [0.59]	-0.7 [-0.84]
Price Differential (Medium/Low)	0.181 [1.37]	-0.02189 [-0.56]	0.06392 [0.30]	1.73 [2.88]***
Price Differential (High/Medium)	-0.171 [-0.72]	-0.08012 [-1.12]	-0.03084 [-0.09]	-0.278 [-0.34]
Agricultural Machinery	0.753 [2.30]**	0.01612 [0.22]	0.696 [1.12]	1.34 [1.14]
Upland Share	0.177 [1.11]	0.08599 [1.77]*	-0.09126 [-0.37]	0.674 [1.71]*
Farm Area	-2.61E-03 [-0.59]	-6.29E-05 [-0.05]	0.0023115 [0.31]	0.0066266 [0.37]
Winter Temperature	0.0162 [0.31]	0.0235 [2.00]**	0.05484 [1.21]	0.111 [0.78]
Winter Temperature Squared	1.39E-03 [0.43]	-0.00061 [-0.73]	0.0019141 [0.46]	-0.009137 [-0.93]
Winter Precipitation	-0.07266 [-1.44]	0.0074889 [0.57]	-0.105 [-0.95]	0.01256 [0.09]
Winter Precipitation Squared	0.0022848	-0.000728	0.01015	-0.01689

	[0.37]	[-0.45]	[0.55]	[-0.83]
Winter Snowfall	0.07173 [0.88]	0.02535 [1.33]	0.203 [1.99]**	-0.323 [-1.41]
Winter Snowfall Squared	-0.01119 [-1.32]	-0.004845 [-2.21]**	-1.40E-02 [-1.24]	2.70E-02 [1.13]
Spring Temperature	0.0004536 [0.00]	0.03506 [1.26]	0.139 [1.07]	0.08682 [0.33]
Spring Temperature Squared	0.0003151 [0.10]	-0.000854 [-1.04]	-0.000361 [-0.10]	-0.000625 [-0.08]
Spring Precipitation	0.0067362 [0.27]	0.0035526 [0.53]	0.05632 [1.57]	-0.01595 [-0.24]
Spring Precipitation Squared	-1.72E-04 [-0.11]	-0.000294 [-0.73]	-0.003862 [-1.59]	0.0034745 [0.87]
Hilly Location	0.0658 [0.92]	0.01152 [0.64]	-0.05525 [-0.72]	-0.458 [-2.09]**
Mountainous Location	-0.448 [-1.57]	-0.05457 [-1.55]	0.898 [2.69]***	0.947 [0.62]
Urban Location	0.07574 [1.68]*	0.0007229 [0.06]	0.08631 [1.18]	-0.00509 [-0.03]
R^2	0.716	0.264	0.188	0.255
Test of weak instruments (H_0: Coefficients of all instruments equal zero)				
F-statistic (p-value)	6.837 (0.000)	2.392 (0.048)	5.708 (0.000)	8.726 (0.000)
***, **, * denote significantly different from zero at 1%, 5%, and 10% significance levels, respectively.				

Note: $N = 3670$.

Table A2. Estimated Coefficients of the System Ordered Fractional Model, Alternative Instrument Specification

Variable	**Quality**		**Quantity**	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Fungicide Expenditure	0.167	0.082 **	0.142	0.045***
Fungicide Expenditure Squared	-0.007	0.009	-0.005	0.004
Insecticide Expenditure	-0.282	0.366	-0.043	0.132
Insecticide Expenditure Squared	-0.066	0.113	0.001	0.045
Herbicide Expenditure	-0.068	0.084	-0.045	0.036
Herbicide Expenditure Squared	0.014	0.012	0.001	0.005
Fertilizer Expenditure	0.045	0.029	0.026	0.011**
Fertilizer Expenditure Squared	0.001	0.002	0.000	0.001
Labor Time	-0.193	0.283	0.125	0.119
Labor Time Squared	0.028	0.054	-0.006	0.026
Wheat Planted Area	-0.025	0.028	-0.016	0.023
Wheat Planted Area Squared	0.000	0.001	0.000	0.001
Chihoku share	-0.399	0.301	-0.494	0.133***
Norin61 share	-0.014	0.174	-0.161	0.058***
Shirogane share	-0.126	0.264	-0.102	0.062
Hokushin share	0.147	0.279	-0.028	0.125
Price Differential (Medium/Low)	0.626	0.376*	0.088	0.147
Price Differential (High/Medium)	0.693	0.535	0.112	0.221
Agricultural Machinery	0.410	1.002	0.240	0.346
Upland Share	-0.777	0.23***0	-0.290	0.107
Farm Area	0.002	0.010	0.005	0.004
Winter Temperature	0.374	0.065***	0.115	0.030
Winter Temperature Squared	0.035	0.007***	0.007	0.002
Winter Precipitation	0.362	0.155**	-0.083	0.061
Winter Precipitation Squared	-0.027	0.025	0.005	0.010
Winter Snowfall	-0.054	0.113	-0.011	0.065
Winter Snowfall Squared	0.014	0.017	0.001	0.011
Spring Temperature	0.983	0.166***	0.378	0.070
Spring Temperature Squared	-0.045	0.005***	-0.018	0.002
Spring Precipitation	-0.091	0.054*	-0.041	0.019**

Spring Precipitation Squared	-0.006	0.004	0.000	0.001
Hilly Location	-0.060	0.083	0.046	0.046
Mountainous Location	0.091	0.319	0.106	0.106
Urban Location	0.139	0.088	0.067	0.028**
First Stage Residuals				
Fungicide Expenditure	-0.119	0.068*	-0.082	0.033**
Insecticide Expenditure	0.601	0.406	0.121	0.151
Herbicide Expenditure	-0.010	0.080	0.039	0.030
Fertilizer Expenditure	-0.069	0.031**	-0.007	0.015
Threshold parameters				
μ_1	-2.392	1.556		
m_2	-0.164	0.070**		
Correlation coefficient between quantity and quality				
ρ_0	0.425	0.046***		
Test of endogeneity (H0: First stage residuals of all potentially endogenous variables equal zero)				
F-statistic	2.23		2.11	
(p-value)	0.06		0.08	
Test of correlated random effects (H0: Farmer-specific averages of all exogenous variables equal zero)				
F-statistic	6.93		4.16	
(p-value)	0.00		0.00	
Observations	3670			
Log likelihood	-6745.13			

Table A3: Marginal Contributions of Inputs to Wheat Value due to Quality, Yield and Overall, Alternative Instrument Specification

Variable	Quality Effect		Quantity Effect		Overall Effect		Quality:Quantity Effect Ratio
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error	
Fungicide Expenditure	1.165	0.520***	6.352	1.841***	7.518	2.192***	0.183
Insecticide Expenditure	-2.298	2.711	-2.075	6.236	-4.373	8.072	1.107
Herbicide Expenditure	-0.145	0.473	-2.063	1.159*	-2.208	1.500	0.070
Fertilizer Expenditure	0.401	0.144***	1.108	0.365***	1.509	0.453***	0.362
Labor Hours	-1.128	1.555	5.579	4.084	4.452	5.009	-0.202
Wheat Planted Area	-0.189	0.188	-0.747	0.947	-0.935	1.093	0.253
Chihoku Share	-3.092	2.309	-24.021	6.456***	-27.113	8.060***	0.129
Norin61 Share	-0.105	1.336	-7.819	2.791***	-7.924	3.530**	0.013
Shirogane Share	-0.977	2.006	-4.974	3.026	-5.951	3.987	0.196
Hokushin Share	1.138	2.134	-1.384	6.051	-0.246	7.468	-0.822
Price Differential (Medium/Low)	4.848	2.853**	4.271	7.154	9.120	9.128	1.135
Price Differential (High/Medium)	5.367	4.096	5.453	10.747	10.821	11.953	0.984
Agricultural Machinery	3.180	7.685	11.653	16.805	14.834	19.384	0.273
Upland Share	-6.017785	1.779***	-14.076	5.197***	-20.0946	6.148***	0.428
Farm Area	0.019	0.073	0.239	0.191	0.258	0.223	0.079
Winter Temperature	5.786	0.808***	9.975	2.116***	15.761	2.644***	0.580
Winter Precipitation	1.818	0.439***	-2.966	1.122***	-1.148	1.359	-0.613
Winter Snowfall	-0.162	0.613	-0.469	2.329	-0.631	2.631	0.346
Spring Temperature	-3.163	0.578***	-10.379	1.552***	-13.542	1.877***	0.305
Spring Precipitation	-1.094	0.218***	-1.976	0.443***	-3.070	0.547***	0.554

***, **, * denote significantly different from zero at 1%, 5%, and 10% significance levels, respectively.